Factors determining soil water heterogeneity on the Chinese Loess Plateau as based on an empirical mode decomposition method

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Abstract: Soil water is a critical resource, and as such is the focus of considerable physical research. Characterization of the distribution and spatial variability of soil water content (SWC) offers important agronomic and environmental information. Estimation of non-stationary and non-linear SWC distribution at different scales is a research challenge. Based on this context, we performed a case study on the Chinese Loess Plateau, with objectives of investigating spatial variability of SWC and soil properties (i.e., soil particle composition, organic matter and bulk density), and determining multi-scale correlations between SWC and soil properties. A total of 86 *in situ* sampling sites were selected and 516 soil samples (0–60 cm depth with an interval of 10 cm) were collected in May and June of 2019 along the Yangling-Wugong-Qianxian transect, with a length of 25.5 km, in a typical wheat-corn rotation region of the Chinese Loess Plateau. Classical statistics and empirical mode decomposition (EMD) method were applied to evaluate characteristics of the overall and scale-specific spatial variation of SWC, and to explore scale-specific correlations between SWC and soil properties. Results showed that the spatial variability of SWC along the Yangling-Wugong-Qianxian transect was medium to weak, with a variability coefficient range of 0.06–0.18, and it was gradually decreased as scale increased. We categorized the overall SWC for each soil layer under an intrinsic mode function (IMF) number based on the scale of occurrence, and found that the component IMF1 exhibited the largest contribution rates of 36.45%–56.70%. Additionally, by using EMD method, we categorized the general variation of SWC under different numbers of IMFs according to occurrence scale, and the results showed that the calculated scales among SWC for each soil layer increased in correspondence with higher IMF numbers. Approximately 78.00% of the total variance of SWC was extracted in IMF1 and IMF2. Generally, soil texture was the dominant control on SWC, and the influence of the three types of soil properties (soil particle composition, organic matter and bulk density) was more prominent at larger scales along the sampling transect. The influential factors of soil water spatial distribution can be identified and ranked on the basis of the decomposed signal from the current approach, thereby providing critical information for other researchers and natural resource managers.

Keywords: bulk density; loess plateau; soil water; soil organic matter; soil texture; spatial variability

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1 Introduction

Soil water, as a critical resource, is the focus of considerable physical research (Xing et al., 2017, 2018). It not only affects runoff generation, erosion and farmland water circulation, but also plays a vital role in the soil-plant-atmosphere continuum and public health issues. Soil water content (SWC) is a critical environmental parameter that has attracted attention from hydrologists and meteorologists for its relevance in the control of water and energy fluxes in soils and at the surface-atmosphere interface (Vereecken et al., 2007; Joiner et al., 2018; Jadidoleslam et al., 2019). Therefore, evaluation of characteristics and dynamics of SWC may be used to inform soil water holding capacity-improvement efforts, hydrological modeling and sustainable agricultural development (Heathman et al., 2012; She et al., 2013; Feki et al., 2018).

SWC exhibits a high spatial variability in correspondence with scale, due to physical, chemical and biological activities within soils (Coppola et al., 2011; Kargas et al., 2016; Peterson et al., 2019). The spatial distribution of SWC is simultaneously affected by inherent soil heterogeneity, as well as extrinsic factors (She et al., 2016; Dari et al., 2019). The multi-scale influence of factors on the distribution and heterogeneity of soil water has been widely assessed using spectral analysis, classical statistical and geostatistical analyses, traditional regression and correlation analyses, and fractal theory (Zeleke and Si, 2006; Si, 2008; Zhao et al., 2016; Xu et al., 2017; Zhao et al., 2017). However, these methods follow the principle of superposition and assume that SWC and related processes are linear. For example, traditional statistical methods are applicable to explore characteristics of soil properties for an entire experimental area, but this method has limitations for smaller sampling scales. Geostatistical analysis typically can be applied only for investigations of specific variables at a single scale. Regression and correlation analyses only consider measured variables, which may be limiting for assessments of complex effects of soil properties on SWC (Arhonditsis et al., 2006). Additionally, although fractal theory solves the single-scale problem, the joint multi-fractal analysis method has limitations due to variability of SWC and soil properties at each scale.

The empirical mode decomposition (EMD) method was adopted in the present study to analyze the relationship between SWC and soil properties at various scales. EMD method and Hilbert spectral analysis can be used in combination to identify the dominant scales of variation for non-stationary and non-linear SWC and to reveal scale-specific controls (Biswas and Si, 2011; Ahmad et al., 2018). Additionally, the controlling factors of SWC distribution and heterogeneity in a horizontal dimension can be used to evaluate soil water movement dynamics (Hu and Si, 2014; Siegfried et al., 2019). These strategies were used for analysis in the present study, and correlations between SWC and soil properties were evaluated using the categorized intrinsic mode functions (IMFs) from the overall spatial pattern of SWC and its influencing factors.

The Loess Plateau extends through arid and semi-arid regions in China, and such loess areas may face environmental threats, e.g., intense soil erosion, severe water scarcity and low vegetation coverage (Liu and Shao, 2016; Pangaluru et al., 2019). SWC is a major limiting factor for agricultural productivity and is the target for environmental protection, and various of soil water may trigger changes in land use/cover, soil desiccation and soil salinization (Wang et al., 2012, 2013; Jia and Shao, 2014; She et al., 2016; Wang et al., 2018; Xing et al., 2019). SWC may also affect other hydrological processes and water balances (Nosetto et al., 2007; Fu et al., 2013). Therefore, SWC on the Chinese Loess Plateau should be assessed and regulated to achieve the long-term sustainable development of the environments. In this context, understanding the scale-dependent relationships of SWC and environmental factors on the Chinese Loess Plateau is imperative.

The objective of this study was to use an EMD method to investigate spatial variability of SWC and soil properties on the Chinese Loess Plateau. Further assessments were conducted to determine the multi-scale effects of factors influencing SWC, and the correlations between SWC and soil properties at different scales.

2 Materials and methods

2.1 Study area and experimental design

The region along the Yangling-Wugong-Qianxian transect (approximately 34°14′06″–34°27′52″N, 107°55′50″–108°24′18″E; 417–536 m a.s.l.) is a typical wheat-corn crop rotation zone. This area is representative of the valley plain on the Chinese Loess Plateau. The climate in this area is warm temperate with monsoons. Specifically, the region is characterized by hot and rainy summers and cold winters with little snow. Annual precipitation is 635.1–663.9 mm and annual mean temperature is 12.9°C–13.1°C. This region is covered by extensive cropland and orchards, as well as small areas of shrubland, floodplain and gully channels. Soil texture of the study area is mainly loamy clay.

The study was conducted in May and June of 2019, and the selected transect was approximately 25.5 km long and encompassed 86 sampling sites (Fig. 1), which were allocated at approximately 300-m intervals in a straight line from north to south (determined using a handheld Global Positioning System). An auger was used for soil sample collection at depths of 0–10, 10–20, 20–30, 30–40, 40–50 and 50–60 cm (total of 516 soil samples). All samples were collected between late May and early June and taken back to the laboratory for measuring SWC, soil organic matter and soil particle composition, using an oven drying method, a titration method and a laser particle analyzer (Mastersizer 2000, Malvern Panalytical Co. Ltd., England), respectively (Bao, 2008). Soil bulk density for the sample at each depth was measured *in situ* using a cutting-ring method (Liang et al., 2018).

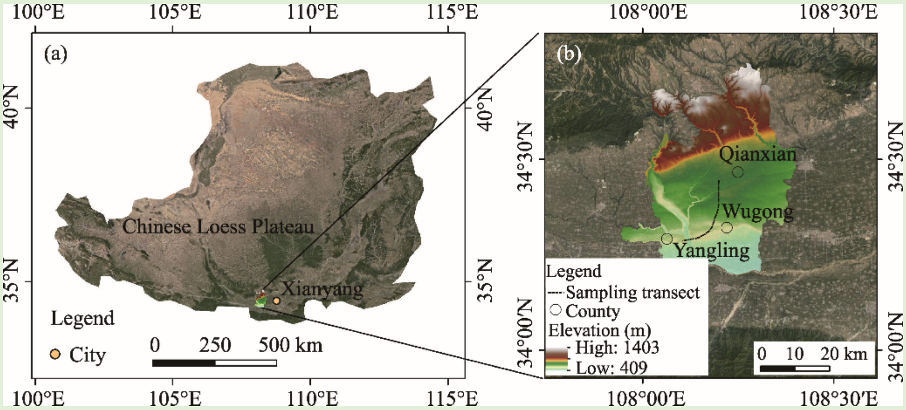

Fig. 1 Location of the study area on the Chinese Loess Plateau (a) and overview of the Yangling-Wugong-Qianxian transect (b)

2.2 Statistical analyses

SWC, soil organic matter, soil particle composition and soil bulk density formed a multivariate data series. The statistical analyses of frequency distribution, normality tests and spatial variability were conducted using Microsoft Excel and SPSS software.

EMD is a relatively new method for analyzing non-linear and non-stationary data. This approach may be used to decompose a signal based on temporal scale features of the data itself, with no presetting of base functions required. In this study, this method was adopted to reveal possible scale-specific relationships between SWC and soil properties. The EMD method decomposed the original spatial data of SWC and soil properties into various spatial scales, which generated various IMFs. Hilbert transformation was conducted for each intrinsic mode function (IMF) to obtain instantaneous frequencies, which were then converted to period and further to spatial scale.

Assuming $D(v)=\{d_1(v), d_2(v), \ldots, d_n(v)\}$ is the n spatial datasets, which is considered as a function of space v. The direction vector along the direction given by angles $f^x=\{f^x_1, f^x_2, \ldots, f^x_{n-1}\}$ in direction set could be denoted as $K^{f^x}=\{k^x_1, k^x_2, \ldots, k^x_n\}$ (x=1, 2, …, m; m is the total number of

direction). The IMFs of the spatial datasets can be obtained by EMD method using the following steps: (1) generating a proper set of direction vectors K; (2) calculating a projection $p^{fx}(v)$ of the spatial datasets $D(v)$ along the direction vectors K^{fx}; (3) finding the spatial instants corresponding to the maxima of projection; (4) interpolating $[v_i^{f_x}, D(v_i^{f_x})]$ to gain envelope curves $e^{fx}(v)$ for all x, and calculating the mean value of the envelopes by Equation 1; and (5) extracting the "detail" $Q(v)$ by Equation 2.

$$M(v)=\frac{1}{m}\sum_{x=1}^{m}\mathrm{e}^{f_x}(v), \tag{1}$$

$$Q(v)=D(v)-M(v). \tag{2}$$

Finally, the above procedure was applied to $D(v)$–$M(v)$ if the "detail" fulfills the stoppage criterion for multivariate IMF; otherwise, the above procedure was applied to $Q(v)$.

3 Results

3.1 Spatial distribution and variation of SWC

The field-average SWC at the depth of 0–60 cm in the study area first increased and then slightly decreased. The maximum value corresponded with the depth of 10–20 cm. The calculated SWC values were approximately 23.00%, 25.47%, 24.55%, 24.05%, 23.32% and 21.55% for depths of 0–10, 10–20, 20–30, 30–40, 40–50 and 50–60 cm, respectively (Table 1). The low topsoil water content was mainly attributed to the fact that the surface soil was exposed to air, and thus was susceptible to water loss. Additionally, the variability coefficient of SWC gradually decreased with soil depth, reaching approximately 0.18, 0.17, 0.15, 0.11, 0.10 and 0.06 for the six soil depths, respectively. This finding indicated that the SWC in the main root zone was medium-to-low, and even low. In general, the 10-cm soil depth layer was the most sensitive to water content due to human or climate factors, and thus the largest variability coefficient corresponded with this topsoil layer. As soil depth increased, soils gradually became less susceptible to human activities or climate, leading to a high stable SWC in the deep soil layers. These characteristics resulted in a decreasing trend for the variability coefficient of SWC, which decreased with increased soil depth (Table 1).

Table 1 Statistical characteristic values of soil water content (SWC)

Soil depth (cm)	SWC				
	Mean (%)	Maximum (%)	Minimum (%)	Standard deviation (%)	Variability coefficient
0–10	23.00	38.05	16.22	4.21	0.18
10–20	25.47	48.43	18.13	4.40	0.17
20–30	24.55	41.85	17.61	3.62	0.15
30–40	24.05	34.38	19.24	2.69	0.11
40–50	23.32	35.73	19.38	2.45	0.10
50–60	21.55	26.55	16.61	1.31	0.06

3.2 Decomposition of SWC

Decomposition of the original signal series of SWC produced a group of IMFs and residues corresponding with the various scales. The IMF revealed changes in oscillation at various scales, and the residue indicated the overall development trend of a complete sequence.

As denoted in Figure 2, for the SWC at the depth of 0–60 cm, IMF1 exhibited the largest range and frequency of oscillations, as well as the highest contribution rates (36.45%–56.70%). The contribution rates exhibited an overall decreasing tendency from IMF1 to IMF5. In addition, according to the occurrence scale, we obtained five IMFs based on the overall variation of SWC for 0–30 and 40–50 cm depths, and four IMFs for 30–40 and 50–60 cm depths. The calculated scales among SWC for each soil layer increased for IMFs with higher numbers. Specifically, the

characteristic scale values varied at the 0–10, 10–20, 20–30, 30–40, 40–50 and 50–60 cm soil depths, with the ranges of 400.00 (IMF1)–1603.85 (IMF5), 363.64 (IMF1)–2754.16 (IMF5), 380.85 (IMF1)–2359.46 (IMF5), 363.64 (IMF1)–1485.42 (IMF4), 363.64 (IMF1)–4239.76 (IMF5) and 371.54 (IMF1)–1625.03 m (IMF4), respectively. The large measurement scale adopted in the present study caused considerable uncertainties of scale. Furthermore, the residues for each soil depth indicated that the tendency of SWC differed among soil layers along the sampling transect. Specifically, the SWC at the depth of 0–20 cm initially increased and then decreased, whereas the SWC at the depth of 20–40 cm initially decreased and then increased. This finding may result from topography, elevation or atmospheric factors, which should be further investigated. The SWC at the depth of 40–60 cm remained stable, which was consistent with the fact that the deep soil layers do not tend to lose as much soil water.

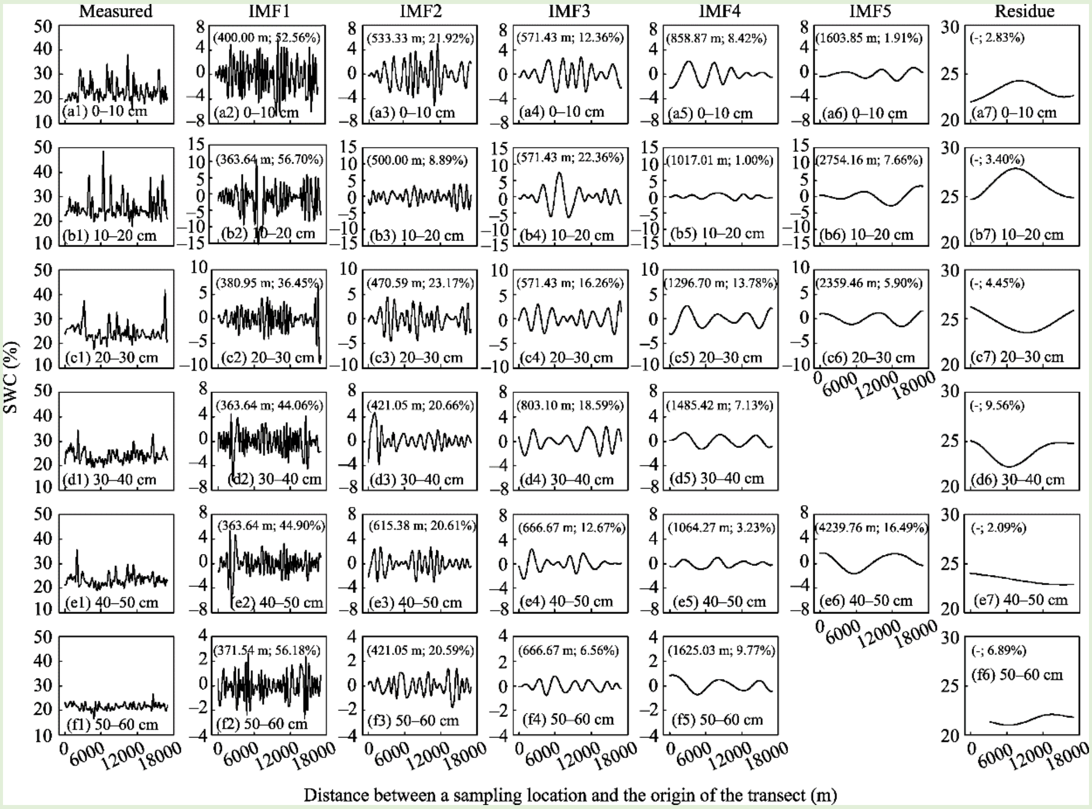

Fig. 2 Intrinsic mode functions (IMFs) and residues of soil water content (SWC) at various soil depths. The numbers in each square bracket, in order, represent the characteristic scale value (m) and the contribution rate (%) of each IMF or residue. -, no value.

After the decomposition of SWC in each soil layer, the correlations of measured SWC with IMFs and residues of SWC among layers were observed (Table 2). Overall, SWC in adjacent layers exhibited significant correlations, which agreed with expectations. Generally, SWC in the shallower layers was significantly correlated with the IMFs of SWC in the upper layers, with a larger contribution rate to the total variance.

3.3 Influence of soil properties on SWC

According to EMD method, lower IMF values correspond with larger-frequency oscillations at smaller scales, whereas larger-scale processes can be represented using higher IMF values extracted at lower-frequency oscillations (Biswas and Si, 2011; She et al., 2013). As illustrated in Figure 3, for mean SWC at the depth of 0–60 cm, approximately 78.00% of the total variance was extracted in IMF1 (scale: 252.86 m) and IMF2 (scale: 438.38 m). Similarly, for soil particle

Table 2 Correlation coefficients of measured SWC with intrinsic mode functions (IMFs) and residues of SWC at different soil depths

	IMFs/residue	10–20 cm	20–30 cm	30–40 cm	40–50 cm	50–60 cm
Decomposition of SWC at the 0–10 cm depth	IMF1	0.852**	0.528*	0.128	0.105	–0.082
	IMF2	0.707*	0.450*	0.055	0.124	–0.055
	IMF3	–0.398	0.467	–0.033	0.111	–0.082
	IMF4	0.569	0.555	0.467	0.250	–1.138
	IMF5	0.463	0.025	–0.074	–0.071	0.051
	Residue	0.362	–0.387	–0.290**	–0.132	–0.238*
	IMFs/residue	20–30 cm	30–40 cm	40–50 cm	50–60 cm	
Decomposition of SWC at the 10–20 cm depth	IMF1	0.787**	0.191	0.031	0.035	
	IMF2	–0.494	–0.199	–0.042	–0.072	
	IMF3	–0.698**	–0.154	–0.040	–0.050	
	IMF4	0.268	0.184	–0.029	–0.034	
	IMF5	0.196	–0.155	–0.186	0.021	
	Residue	–0.397	–0.309**	–0.164	–0.273*	
	IMFs/residue	30–40 cm	40–50 cm	50–60 cm		
Decomposition of SWC at the 20–30 cm depth	IMF1	0.654**	0.517	0.117		
	IMF2	0.628*	0.551*	0.055		
	IMF3	0.627	–0.524	0.117		
	IMF4	0.273	0.342	–0.183		
	IMF5	0.137	0.331	0.138		
	Residue	0.322*	0.139	0.159		
	IMFs/residue	40–50 cm	50–60 cm			
Decomposition of SWC at the 30–40 cm depth	IMF1	0.517**	0.340			
	IMF2	0.413	0.248			
	IMF3	0.423	–0.233			
	IMF4	0.641*	0.145			
	Residue	0.546*	0.329			
	IMFs/residue	50–60 cm				
Decomposition of SWC at the 40–50 cm depth	IMF1	0.349*				
	IMF2	0.156				
	IMF3	–0.143				
	IMF4	0.024				
	IMF5	0.342**				
	Residue	–0.079				

Note: *, significant difference at $P<0.05$ level; **, significant difference at $P<0.01$ level.

composition at the depth of 0–60 cm, approximately 84.00% of the total variance of clay, 60.00% of the total variance of silt and 67.00% of the total variance of sand were extracted in IMF1 and IMF2. For soil organic matter and bulk density, approximately 62.00% and 63.00% of the total variance were extracted in IMF1 and IMF2, respectively. Additionally, a greater variation was observed in the residues of clay (10.43%), silt (16.17%) and sand (13.94%) than in the residues of soil organic matter (5.36%) and bulk density (0.42%). This finding may reflect the insufficiency of EMD method for application to soil texture data to determine scales greater than the measurement transect length (approximately 25.5 km in the present study). Furthermore, the sum of contribution rates to the total variance of all IMFs and residues was 100.00%, which indicated that soil water processes could operate independently at various IMFs.

Table 3 presents the correlation coefficients of soil properties with IMFs and residue of average SWC for the depth 0–60 cm. Overall, soil particle composition, organic matter and bulk density

were significantly correlated with SWC. Specifically, the correlation coefficients of SWC and clay, silt and sand contents exhibited significant differences (P<0.01) in all IMFs. This finding indicated that soil particle composition exhibited a substantial influence on SWC. Soil organic matter played a scale-specific role in determining SWC, as indicated by a significant difference (P<0.05) of soil organic matter in IMF1 and IMF2, and a highly significant difference (P<0.01) of soil organic matter in IMF3 and IMF4. In general, soil organic matter plays a dominant role in maintaining soil productivity and supports the enhancement of vegetation and physical properties of soils (Körschens, 2002), which contribute to water storage. Soil bulk density also exhibited a critical scale-specific effect on SWC, as indicated by the significant correlations in IMF2 and IMF4; however, the relationship was not significant in IMF1 and IMF3.

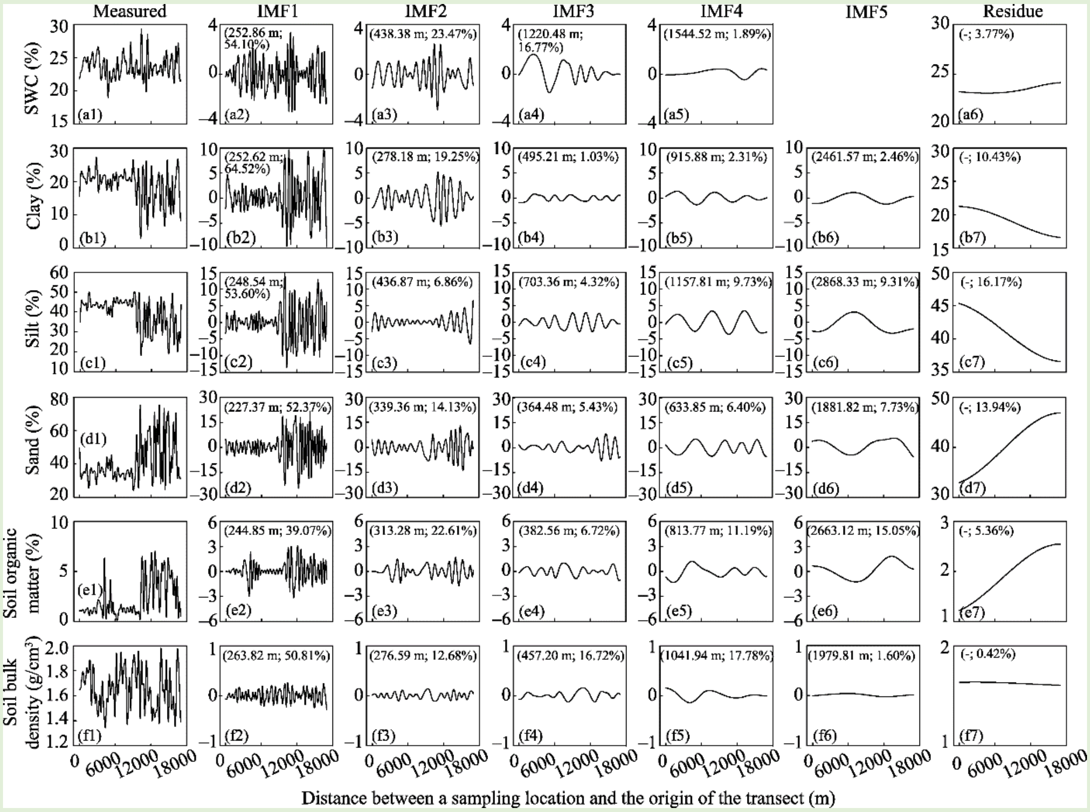

Fig. 3 Intrinsic mode functions (IMFs) and residues of mean SWC and soil properties (soil particle content, organic matter and bulk density) at the soil depth of 0–60 cm. The numbers in each square bracket, in order, represent the characteristic scale value (m) and the contribution rate (%) of each IMF or residue. -, no value.

Table 3 Correlation coefficients of soil properties with IMFs and residue of mean SWC at the depth of 0–60 cm

IMFs/residue	Clay	Silt	Sand	Soil organic matter	Soil bulk density
IMF1	0.520**	0.508**	–0.514**	0.411*	0.159
IMF2	0.589**	0.605**	–0.592**	0.501*	0.431*
IMF3	0.672**	0.669**	–0.665**	0.545**	0.363
IMF4	0.714**	0.705**	–0.706**	–0.582**	–0.689**
Residue	–0.847**	–0.840**	0.433**	0.463**	–0.973**

Note: *, significant difference at P<0.05 level; **, significant difference at P<0.01 level.

Medium-to-strong correlations were observed between SWC and soil properties, and the correlation coefficients were generally larger than 0.500. These coefficients exhibited an overall increasing tendency for IMFs with higher values (Table 3). This result implied that the effects of

soil particle composition, organic matter and bulk density on SWC became increasingly crucial as the calculated scale increased from 252.86 to 1544.52 m. Furthermore, the absolute value of the correlation coefficients between SWC and soil particle content were larger than those between SWC and soil organic matter and bulk density, suggesting a deterministic effect of soil particle composition on SWC.

4 Discussion

Research on the spatial variations of soil water and its controlling factors is of theoretical and practical significance. In this study, SWC and its determining factors were investigated along the Yangling-Wugong-Qianxian transect in a typical wheat-corn crop rotation zone on the Chinese Loess Plateau, as based on the EMD method. Some gaps existed between soil properties and the original signal and components of soil water. Reasons are discussed in the following paragraphs.

This study explored the heterogeneity of soil water based on a single time scale (i.e., dry season). Entin et al. (2000) and Yao et al. (2016) indicated that the correlation scale of surface soil moisture is slightly less than two months, and soil moisture is more stable in dry season than in rainy season. Therefore, the sampling in this study was conducted in May and June to reflect these facts. For this study, no rain occurred before sampling, further creating consistent background conditions; more background environmental variations may have led to different results.

Many field experiments have been conducted on the Chinese Loess Plateau to reveal spatial and temporal distributions of soil water (He et al., 2019; Liang et al., 2019; Zhao et al., 2019; Yu et al., 2020), while influences of soil physical properties on SWC were seldomly been studied. Geostatistics have also been used to assess heterogeneity of surface soil water (Zou et al., 2019); however, the analysis of SWC using this method was greatly affected by spatial scale (Lian et al., 2019). Given such shortcomings, we combined EMD method with classical statistics in this research to evaluate the spatial distribution of SWC with respect to specific scales, and assessed effects of soil particle composition, organic matter and bulk density on SWC.

Kong et al. (2017) indicated that SWC varied with sampling scales. In this study, a 25.5-km transect on the Chinese Loess Plateau was selected for sampling to analyze the spatial variation of soil moisture. Further studies should focus on different sampling scales in this region. Stepwise multiple linear regressions may be utilized to predict SWC in each IMF based on scale-specific controlling factors in the same IMF. Prediction of SWC using EMD method is expected to outperform that based on the original data. As Simbahan and Dobermann (2006), Kerry and Oliver (2007), Lai et al. (2017) and Cai et al. (2019) have reported, sampling size and design had a great influence on estimating spatial variability of the soil variables related to SWC. Further, the distribution and heterogeneity of soil water in the vertical dimension also warrants attention.

Tillage type is also an important factor affecting variation of SWC. Gravel and film mulching, for instance, are typical agricultural approaches in the study region. They significantly influence soil water movement due to variations in the soil surface (Zhao et al., 2017; Zhang et al., 2019). However, in this study, the coverage of gravel or plastic film was not considered. In future research, soil water movement under these tillage types needs to be considered.

Land use type is another factor influencing SWC and soil physical properties (Neris et al., 2012). Forests, shrubland and cropland have different effects on the distribution and heterogeneity of soil water. As such, soil water varies with terrain and vegetation, which should be considered in soil water prediction in future studies. With the development and application of "3S" technology, satellite remote sensing image can be used to estimate soil moisture on large scales, due to its convenient measurement and high accuracy. For long-term measurements of soil properties, Schneider et al. (2008), Zhao et al. (2017) and Xing et al. (2019) introduced time stability analysis to identify fixed points for monitoring on large scales. As a consequence, for such a large region on the Chinese Loess Plateau, time stability analysis may also be adopted for long-term periodic monitoring, which would provide scientific basis for soil management and soil water conservation.

5 Conclusions

Empirical mode decomposition method was shown to separate overall variation in SWC and various soil properties into different numbers of IMF according to scale of occurrence; thereafter, the dominant controls on SWC could be identified. We then categorized the general variation of SWC under different numbers of IMF based on scale of occurrence, and the results showed that calculated scales among the SWC for each soil layer increased in correspondence with higher IMF numbers. Moreover, soil texture was found to be a dominant factor in control of SWC. Influence of three soil properties (soil particle composition, organic matter and bulk density) were more effective in predicting SWC at larger scales along the sampling transect (Yangling-Wugong-Qianxian) on the Chinese Loess Plateau.

Therefore, SWC distribution can be predicted using the scale-specific soil water and soil properties. This study has contributed to our understanding on the determination of dominant factors influencing soil water heterogeneity. The results can be effectively used to predict SWC from a few dominant factors, providing a more efficient framework to develop and monitor land management initiatives.

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